The Impact of Credit Scoring on Credit Spreads and Consumption over the Business Cycle*

Matthew N. Luzzetti† and Seth Neumuller‡

March 18, 2015

Abstract

Spreads on unsecured consumer debt are volatile, countercyclical, and rise persistently following recessions. We study the determination of credit spreads over the business cycle using a quantitative equilibrium model of consumer default with countercyclical income risk. In our model, lenders employ backward-looking credit scoring techniques to form expectations about future charge-off rates and set credit spreads, as is done in practice. This innovation allows our model to match many key features of the data that standard models of consumer default do not. We demonstrate that credit scoring slows recoveries in consumption following recessions, but reduces average consumption volatility.

JEL Classifications: G21, E44, E51, D84
Keywords: Consumer Debt, Credit Spread, Credit Scoring, Consumption Volatility

*We would like to thank Kyle Herkenhoff, Lee Ohanian, Casey Rothschild, Daniel Sichel, and Akila Werapana for helpful comments and suggestions. All remaining errors are our own.

†matthew.luzzetti@db.com; Deutsche Bank Securities Inc., 60 Wall Street, New York, NY 10005.

‡Corresponding Author: seth.neumuller@wellesley.edu; (781) 283-2669; Department of Economics, Pendleton East, Wellesley College, 106 Central Street, Wellesley, MA 02481.

1 Introduction

The unsecured credit market is the marginal source of finance for many consumers.[1] Consistent with this view, the credit spread on unsecured consumer debt is significantly negatively correlated with real personal consumption expenditures (-0.64), as depicted in Figure 1. Thus, understanding the determination of credit spreads on unsecured consumer debt likely has important welfare implications.

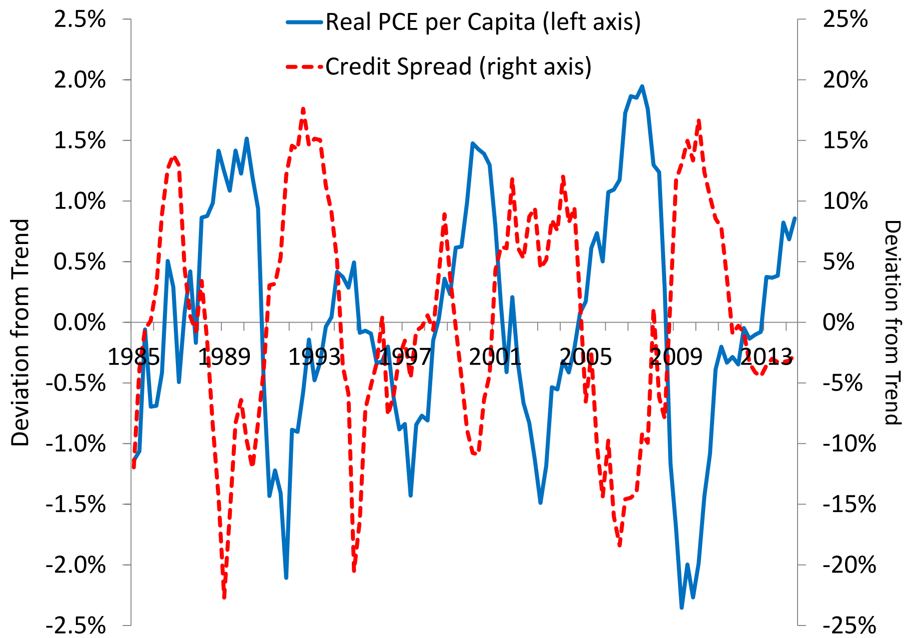


Figure 1. Cyclical components of real personal consumption expenditures (PCE) per capita (Source: Bureau of Economic Analysis, NIPA) and the credit spread on unsecured consumer debt, the latter of which is defined as the interest rate on credit card plans at commercial banks (Source: Board of Governors, G.19) minus the interest rate on 1-year constant maturity Treasury bills (Board of Governors, H.15). Both series detrended using the Hodrick-Prescott Filter with smoothing parameter equal to 1,600.

Despite the important role for credit spreads in consumption smoothing over the business cycle, there remains a fundamental tension between how spreads on unsecured consumer debt are determined in practice and how they are modeled in existing quantitative models of the unsecured consumer credit market. In practice, lenders routinely forecast the credit risk of applicants by using a truncated set of historical data to regress past loan performance on ob-

[1]Sullivan (2008) finds that low-asset households increase credit card debt by more than \$0.11 per dollar of earnings lost in response to an unemployment spell, while Gross and Souleles (2002) estimate that the elasticity of credit card debt to interest rates is approximately -0.85.

servables such as income, age, and FICO score – a practice known as credit scoring.[2] These results are then used to set interest rates on unsecured debt contracts.[3] The backward-looking nature of credit scoring, however, stands in stark contrast to the assumption that lenders have rational expectations about future charge-off rates, as is standard in models of consumer default derived from the seminal work of Chatterjee, Corbae, Nakajima, and Rios-Rull (2007) and Livshits, MacGee, and Tertilt (2007). In this paper, we ask whether rational expectations or credit scoring is better able to account for the business cycle properties of the unsecured consumer credit market.

We begin by documenting several salient business cycle facts about the unsecured consumer credit market. Much like the credit spread, we document that the charge-off rate on unsecured consumer debt is highly volatile and strongly countercyclical. We also find that unsecured debt is modestly countercyclical. Finally, using a fitted vector autoregression model, we show that a one-time increase in the charge-off rate leads to a delayed and persistent rise in the credit spread, with a peak response three quarters after the initial shock, and a protracted decline in consumption.

To better understand these facts, we introduce credit scoring into an otherwise standard quantitative equilibrium model of consumer default with countercyclical income risk. We then compare this model's cyclical behavior to an alternative economy in which lenders have rational expectations about future charge-off rates, as is standard in the literature. We find that a calibrated version of the model with credit scoring outperforms its rational expectations counterpart in reproducing a number of key cyclical features of the unsecured consumer credit market. Specifically, the model with credit scoring more closely matches the volatility of debt and spreads, the countercyclical nature of debt, and the contemporaneous correlation between spreads and consumption and spreads and output. But perhaps the most significant outperformance of the model with credit scoring is observed in its intertemporal dynamics. Credit scoring substantially improves the model's ability to capture the lead-lag correlations of debt with output and allows the model to replicate the hump-shaped, persistent response of the credit spread following a one-time shock to the charge-off rate. These dynamics are not present in the model with rational expectations. On the other hand, we find that credit scoring has little effect on the long-run performance of the model economies, as a similar calibration in each model is able to match the average debt-income

[2]Credit scoring is the process by which lenders forecast the credit risk of a potential borrower using information about the repayment history of other borrowers with similar observable characteristics. This is distinct from an individual's *credit score*, which also provides information to lenders about the creditworthiness of a potential borrower, but is solely determined by the individual's *own* repayment history and existing liabilities.

[3]See Thomas (2000) for an overview of credit scoring practices in the unsecured consumer credit market.

ratio and bankruptcy filing rate found in the data. Thus, while rational expectations may serve as a useful benchmark for modeling the determination of credit spreads over the long run, modeling the credit scoring methods used by lenders in practice allows the model to better match the data along a number of dimensions.

In the model with rational expectations, credit spreads continuously adjust to fully reflect the true default risk posed by each borrower. The countercyclical nature of income risk generates large countercyclical fluctuations in the charge-off rate. As a result, credit spreads rise sharply and remain elevated as long as the economy is in a recession, and spreads return immediately to their expansion-consistent, pre-recession levels as soon as the economy recovers. Higher spreads in recessions discourage borrowing, while lower spreads in expansions encourage borrowing. For this reason, unsecured debt in the model with rational expectations is strongly procyclical rather than weakly countercyclical as in the data. The strong state-dependence of the credit spread produces contemporaneous correlations between many variables that exceed their data counterparts (in an absolute value sense). This is especially true for the credit spread. Moreover, the immediacy of the response of spreads to aggregate shocks means that the model fails to generate persistence in the response of the credit spread and consumption to a one-time increase in the charge-off rate. A corollary of these results is that unsecured debt is a poor instrument for consumption smoothing purposes in this environment, as the cost of borrowing rises (i.e. spreads increase) at the same time as the desire to borrow (i.e. during recessions).[4]

Conversely, in the model with credit scoring, lenders form expectations about future charge-off rates based on the history of realized charge-off rates for similar loan contracts. Lenders then adjust their expectations over time in response to forecast errors. We find that the interaction between this adjustment process and countercyclical income risk allows the model to produce more realistic business cycle dynamics. In the model with credit scoring, lenders react to a higher charge-off rate during a recession by revising upward their beliefs about future charge-off rates, causing credit spreads to rise to compensate for higher expected losses. If the recession persists, charge-off rates continue to exceed expectations, leading to further increases in the credit spread. However, because of the history dependence of the spread induced by credit scoring, the credit spread remains elevated even after the economy recovers and the charge-off rate declines. Therefore, history dependence in the credit spread reduces the contemporaneous link between the spread and the aggregate state of the economy. This persistence allows the model to reproduce the hump-shaped response of the spread to a one-time shock to the charge-off rate that is found in the data.

To see why credit scoring is responsible for these dynamics, note that history dependence

[4]This is consistent with the findings of Athreya, Tam, and Young (2009) for this class of models.

causes spreads to be initially lower (higher) when the economy first transitions to a recession (expansion), than they would be without credit scoring. A higher cost of debt during expansions reduces the level of debt, and vice versa, allowing the model to reproduce countercyclical movements in debt. This same mechanism also helps reduce the excess comovement that arises when creditors use rational expectations to set spreads. Given the choice between the credit scoring and rational expectations environments, consumers overwhelmingly prefer the former. By breaking the tight link between aggregate economic conditions and credit spreads that is characteristic of the rational expectations environment, unsecured debt becomes a more effective tool to smooth consumption. In fact, consumption is 22% less volatile when lenders use credit scoring practices to set spreads than when lenders have rational expectations.

Although there is an extensive literature that uses quantitative equilibrium models of consumer default to study the unsecured credit market, most studies focus on either bankruptcy reform or the secular rise in unsecured debt and bankruptcies that occurred during the Great Moderation.[5] Until recently, comparatively little attention has been given to the business cycle properties of the unsecured consumer credit market. Fieldhouse, Livshits, and MacGee (2014) demonstrate that a standard model of consumer default with countercyclical income risk, calibrated at an annual frequency, fails to generate realistic fluctuations in bankruptcies and unsecured debt without large intermediation shocks. Nakajima and Rios-Rull (2014) study a general equilibrium model of consumer default with countercyclical persistent income risk, also calibrated at an annual frequency, and demonstrate that their model is capable of reproducing much of the co-movement between output, consumption, investment, and bankruptcies.[6] While these existing studies attempt to bridge the gap between standard models of consumer default and the traditional business cycle literature, our main contribution is to demonstrate that the way in which lenders form expectations about future charge-off rates has important implications for both welfare and the ability of standard models to fit the data.[7] In particular, we find that credit scoring reduces the volatility of credit spreads, thereby improving the efficacy of unsecured debt as a consumption smoothing device.[8]

We model the evolution of lenders' beliefs about future charge-off rates using an adaptive

[5]See, for example, Drozd and Nosal (2008), Livshits, MacGee, and Tertilt (2010), Sánchez (2010), Athreya, Tam, and Young (2012), and Luzzetti and Neumuller (2014), among others.

[6]Gordon (2014) also studies a general equilibrium model of consumer default with countercyclical income risk, but his primary focus is evaluating the welfare costs of alternative bankruptcy regimes.

[7]There is also a large literature that explores cyclical variations in corporate bond spreads. See, for example, Gourio (2013) and references therein.

[8]Herkenhoff (2014) argues that increased access to credit since the start of the Great Moderation has improved welfare by reducing the consumption volatility of unemployed households, while Nakajima and Rios-Rull (2014) argue that improving access to the unsecured credit market actually increases consumption volatility over the business cycle. Lenders have rational expectations in both models.

learning algorithm as in Evans and Honkapohja (2001). Our paper thus contributes to the nascent literature exploring the implications of adaptive learning in quantitative macroeconomic settings.[9] This is not the only paper, however, to consider adaptive learning in a quantitative model of consumer default. Luzzetti and Neumuller (2014) study the ability of learning about the likelihood and persistence of recessions during the Great Moderation to account for the observed growth in unsecured consumer debt and bankruptcies. Our current paper differs from this contemporaneous study in two important respects. First, this paper considers learning about default rates instead of learning about idiosyncratic income risk. Second, we focus on the cyclical properties of the unsecured consumer credit market and, in particular, on the determination of credit spreads and related implications for consumption.

The remainder of this paper is organized as follows. Section 2 documents the business cycle properties of the unsecured consumer credit market. Section 3 describes our quantitative equilibrium model. Section 4 outlines our calibration strategy for taking our model to the data. Section 5 presents our main quantitative results. Finally, Section 6 concludes.

2 Empirical Facts

The unsecured consumer credit market has changed dramatically since the early 1980's. Use of unsecured debt nearly doubled, bankruptcy filing rates quadrupled, and the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 increased the costs associated with debt relief. Moreover, the 2008–'09 recession was one of the worst on record, resulting in more than a 20% decline in the average unsecured debt to income ratio. For these reasons, we focus on the period beginning in the early 1990's and ending in early 2005, just prior to implementation of the BAPCPA and well before the start of the 2008–'09 recession. Specifically, our empirical analysis uses quarterly data from 1990:Q1 through 2005:Q1 on real GDP per capita, real personal consumption expenditures per capita, real unsecured debt per capita, the charge-off rate on credit card loans, and the credit spread on credit card loans. We define the credit spread as the interest rate on credit card plans minus the interest rate on 1-year constant maturity Treasury bills.[10] We isolate the cyclical component of each time series using the Hodrick–Prescott filter with a smoothing parameter of 1,600.

Table 1 reports the relative volatility and contemporaneous correlations between our variables of interest. Unsecured consumer debt is about three times more volatile than real

[9]Prominent examples include Eusepi and Preston (2011) who study a real business cycle model and Carceles-Poveda and Giannitsarou (2008) and Adam and Marcet (2011) who explore the implications for asset prices.

[10]We show in the Appendix that the empirical facts documented here for the 1990:Q1 to 2005:Q1 time period are similar to those for the entire 1985:Q1 to 2014:Q2 period for which data is currently available.

GDP per capita, while the credit spread and charge-off rate are about nine and fifteen times more volatile than real GDP per capita, respectively. Moreover, consumption is negatively correlated with both the charge-off rate (-0.69) and the credit spread (-0.49), while the charge-off rate and credit spread are positively correlated with each other (0.64). Consistent with its use for consumption smoothing purposes, we find that unsecured debt is weakly negatively correlated with both output (-0.12) and consumption (-0.22), suggesting that debt levels tend to rise during recessions and fall during expansions.[11] Figure 2 plots the correlations of the charge-off rate, credit spread, and unsecured debt with real GDP per capita for various lead and lag times. While both the charge-off rate and credit spread are countercyclical, unsecured debt lags the cycle by approximately 7 quarters.

Table 1: Business Cycle Properties of the Unsecured Consumer Credit Market

	Relative	Contemporaneous Correlations				
	Volatility	Output	Consumption	Debt	Spread	Charge-offs
Output	1.00	1.00	0.86	-0.12	-0.56	-0.57
Consumption	0.83	0.86	1.00	-0.22	-0.49	-0.69
Debt	2.96	-0.12	-0.22	1.00	-0.30	0.20
Spread	8.77	-0.56	-0.49	-0.30	1.00	0.64
Charge-offs	14.8	-0.57	-0.69	0.20	0.64	1.00

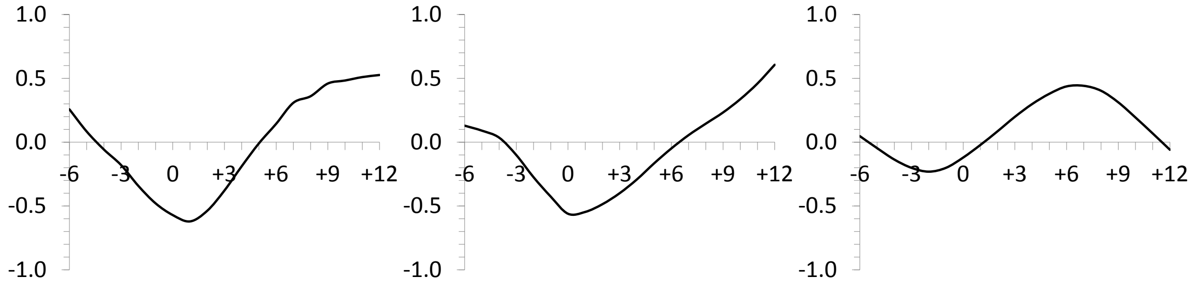
Note: Cyclical components of quarterly data isolated using Hodrick-Prescott filter with smoothing parameter equal to 1,600. Output: real GDP per capita. Consumption: real personal consumption expenditures per capita. Debt: total real revolving unsecured consumer credit outstanding per capita. Spread: interest rate on credit card plans at commercial banks minus the interest rate on 1-year constant maturity Treasury bills. Charge-offs: charge-off rate on credit card plans.

We explore the empirical dynamic relationships between the charge-off rate, credit spread, and consumption further by estimating the following three-variable vector autoregression using the cyclical components of each detrended time series:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{1}$$

where $y_t = [\text{Charge-off}_t,\ \text{Spread}_t,\ \text{Consumption}_t]'$, $\mathbb{E}[u_t] = 0$, $\mathbb{E}[u_t u_t'] = \Sigma$, and $\mathbb{E}[u_t u_s'] = 0$ for $t \neq s$. We select a lag length p equal to two, which leaves us with a total of 59 quarterly

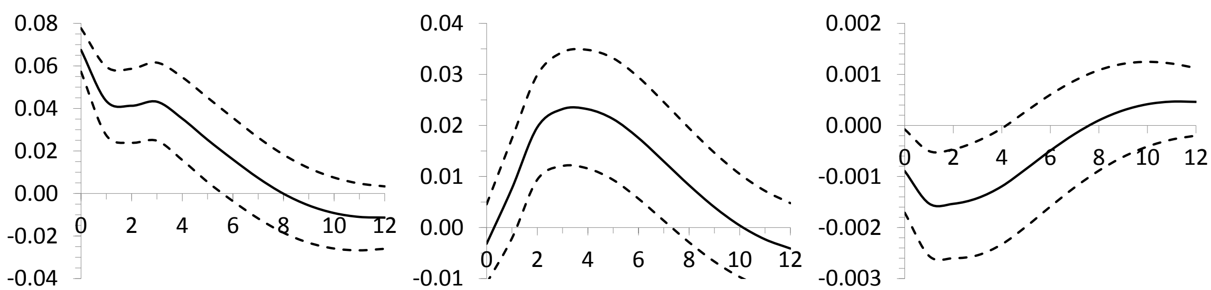
[11] Using annual data, Fieldhouse et al. (2014) find that the correlation between debt and output depends on the time period of study, ranging from strongly procyclical from 1973 through 2012, to countercyclical between 1993 and 2006. Nakajima and Rios-Rull (2014), also using annual data, report that debt was marginally procyclical during the 1980 to 2013 period.



(a) Charge-off Rate (b) Credit Spread (c) Unsecured Debt

Figure 2. Lead and lag correlations with real GDP per capita.

observations in our sample. Orthogonalized impulse response functions for a one standard deviation shock to the charge-off rate are depicted in Figure 3. Panel (a) conveys persistence in the charge-off rate at a quarterly frequency, as the initial shock takes about 8 quarters to fully dissipate. From Panel (b) we see that the credit spread exhibits a delayed, persistent response to an increase in the charge-off rate, peaking 3 to 4 quarters after the initial shock at 2.3% above trend, and remaining elevated for 10 quarters. The shape of this impulse response function suggests that lenders react to an increase in the charge-off rate by raising interest rates. Finally, Panel (c) demonstrates that these dynamics in the unsecured consumer credit market have important implications for consumption, which falls by nearly 0.2% in the quarter following the initial shock and takes nearly 8 quarters to fully recover.



(a) Charge-off Rate (b) Credit Spread (c) Consumption

Figure 3. Response to a one time, one standard deviation increase in the charge-off rate. Dotted lines represent 90% confidence interval.

3 Model

To better understand how credit spreads on unsecured debt are determined and their associated macroeconomic implications, we construct a quantitative equilibrium model of the unsecured consumer credit market that draws heavily upon the canonical frameworks developed by Chatterjee et al. (2007) and Livshits et al. (2007). The model economy is populated by overlapping generations of J-period lived consumers. Each generation is comprised of measure one of consumers facing countercyclical idiosyncratic income risk during their working life. Markets are incomplete as the only assets available for consumption smoothing purposes are one-period, non-contingent, pure discount bonds that are bought and sold by a risk-neutral and competitive financial intermediary. Consumers have the option to declare bankruptcy, and therefore cannot commit to repay their debt obligations. As a result, the financial intermediary must charge a spread above the risk-free rate on consumer debt contracts in order to compensate for expected losses. We consider two versions of our model that are identical except for how we model creditor expectations about losses on debt contracts. As is standard in the literature, the financial intermediary has rational expectations about future charge-off rates in the first version, while the financial intermediary uses credit scoring to forecast future charge-off rates in the second version, consistent with lender practices.

3.1 Consumers

Consumers maximize expected discounted life-time utility from consumption at each age j:

$$\mathbb{E}_j \sum_{a=j}^{J} \beta^{a-j} u(c_a), \tag{2}$$

where $\beta \in (0,1)$ is the discount factor, c_a is consumption at age a, $\mathbb{E}_j$ is the expectation operator taken with respect to information at age j, and $u(\cdot)$ is twice continuously differentiable and strictly concave. Consumers receive an idiosyncratic endowment of the consumption good $y_{i,a,t}$ each period. During their first N periods of life (*working life*), the log of each consumer's endowment is given by

$$\ln(y_{i,a,t}) = \Upsilon_{s_t} + \ln(f_a) + z_{i,t} + e_{i,t}, \tag{3}$$

where Υ_{s_t} is the aggregate component of income which varies with the aggregate state s_t and f_a is a deterministic function of age. Since we intend for the aggregate state to capture periods of expansion and contraction in economic activity, we assume that s_t evolves according to a first-order Markov chain with Markov transition matrix Π. The transitory component of income $e_{i,t}$ is i.i.d. $N\left(-\frac{1}{2}\sigma_e^2, \sigma_e^2\right)$, while the persistent component of income $z_{i,t}$ evolves according to

$$z_{i,t} = \rho z_{i,t-1} + \zeta_{i,t}\varepsilon_{i,t}, \tag{4}$$

where the persistent shock $\varepsilon_{i,t}$ is i.i.d. $N\left(-\frac{1}{2}\sigma^2_{\varepsilon,s_t}, \sigma^2_{\varepsilon,s_t}\right)$ and the volatility of persistent shocks σ_{ε,s_t} is allowed to vary over the business cycle. Consumers receive a persistent shock with probability ξ each period. It follows that $\zeta_{i,t}$ is equal to 1 with probability ξ and 0 otherwise. During their final $J-N$ periods of life (*retirement*), the log of each consumer's endowment evolves according to

$$\ln(y_{i,a,t}) = \ln(f_a) + z_{i,N}, \tag{5}$$

where $z_{i,N}$ is the persistent component of income at retirement. Thus, we assume that retirees are not subject to income shocks.

3.2 Credit Market

A risk-neutral and competitive financial intermediary buys and sells one-period, non-contingent, pure discount bonds at price $q_t(b', a, z; s)$, where b' is the face value to be repaid at date $t+1$ by a consumer age a with persistent component of income z given aggregate state s at date t. The intermediary can borrow and lend on world capital markets at the risk-free real interest rate r. Since consumers cannot commit to repay, $q_t(b', a, z; s)$ must compensate the financial intermediary for expected losses in addition to the cost of funds. We use the convention that $b' < 0$ ($b' > 0$) represents a consumer who is selling (buying) bonds.

3.3 Bankruptcy

Consumers with outstanding debt obligations have the option to declare bankruptcy, which we model after Chapter 7 of the U.S. bankruptcy code.[12] Under Chapter 7, certain assets can be shielded from creditors using personal exemptions covered under federal bankruptcy law or the laws of the debtor's home state.[13] In terms of our model, bankrupts must pay a fixed cost related to court filing costs and lawyer fees and relinquish all assets in excess of the personal exemption limit. In addition, bankruptcy is typically viewed by creditors

[12] The U.S. bankruptcy code offers consumers two choices when filing for bankruptcy protection: Chapter 7 and Chapter 13. A consumer that chooses to file under Chapter 7 is relieved of all outstanding debt obligations in exchange for their assets net of any personal exemptions. A consumer that chooses to file under Chapter 13, on the other hand, agrees to pay back a portion of their outstanding debt obligations over a 3-5 year period in exchange for the ability to keep their assets. In either case, a bankruptcy flag is maintained on their credit report for a period of 10 years. The conditions of bankruptcy in our model are chosen to match Chapter 7 of the U.S. bankruptcy code, which accounts for approximately 70% of bankruptcy filings over the period under consideration. Moreover, given the choice between Chapters 7 and 13, a consumer would only choose Chapter 13 if they have assets that they would like to keep but would otherwise lose by filing under Chapter 7. Since there is only one asset in our model, bankrupts will inevitably have a negative asset position, and therefore will always prefer to file under Chapter 7.

[13] See www.uscourts.gov/FederalCourts/Bankruptcy/BankruptcyBasics/Chapter7.aspx for details.

as an adverse signal about a consumer's future ability to repay their debt. Consequently, access to credit for consumers that have recently declared bankruptcy may be available on prohibitively tough terms or may not be available at all.[14] Motivated by these observations, bankrupts in our model have their debt obligations extinguished in exchange for temporary exclusion from credit markets and a one-time resource cost

$$\nu_{i,a,t} = \max\{y_{i,a,t} - \psi, 0\} + \phi, \tag{6}$$

where ψ is the personal exemption limit and ϕ represents court costs and lawyer fees. We assume that bankrupts are permitted to re-enter credit markets with probability $\theta \in (0, 1)$ in each subsequent period.

3.4 Problem of a Consumer

We now recursively formulate the problem of a consumer. In order to reduce the computational burden involved in solving for a competitive equilibrium when lenders use credit scoring to form expectations about future charge-off rates, we assume that consumers maximize *anticipated utility* as in Kreps (1998) and Sargent (1999). This means that consumers re-optimize at each date t assuming that the current equilibrium bond pricing schedule will remain constant into the indefinite future.[15] Solving for a competitive equilibrium when lenders have rational expectations about future charge-off rates is the special case in which the equilibrium bond price schedule is actually constant.

The problem of a consumer age $a \leq N$ at date t with access to credit markets, current bond holdings b, transitory component of income e, and persistent component of income z given aggregate state s is then

$$V_t(b, a, e, z; s) = \max\left\{P_t(b, a, e, z; s), B_t(a, e, z; s)\right\} \tag{7}$$

where the value of remaining in good credit standing is

$$P_t(b, a, e, z; s) = \max_{b' \in \mathbb{R}} u(y(a, e, z; s) + b - q_t(b', a, z; s)b') + \beta \mathbb{E}_t\left[V_t(b', a', e', z'; s') | z; s\right], \tag{8}$$

[14] Musto (2004) finds this effect lasts until the bankruptcy flag is removed from a consumer's credit report. Jagtiani and Li (2014) find that while credit demand recovers quickly after bankruptcy, credit supply remains limited for a long period of time after discharge.

[15] Solving for the exact Bayesian solution requires including the bond price schedule as a state variable. Cogley and Sargent (2008) show that under certain conditions anticipated utility provides a close approximation to the exact Bayesian solution.

the value of declaring bankruptcy is

$$B_t(a,e,z;s) = u\left(y(a,e,z;s) - \nu(a,e,z;s)\right) + \beta \mathbb{E}_t\left[X_t(0,a',e',z';s')|z;s\right], \tag{9}$$

and the value of being excluded from credit markets is

$$\begin{aligned} X_t(b,a,e,z;s) = \max_{b' \in \mathbb{R}_+} & u\left(y(a,e,z;s) + b - q_t(b',a,z;s)b'\right) \\ & + \beta \mathbb{E}_t\left[\theta V_t(b',a',e',z';s') + (1-\theta)X_t(b',a',e',z';s')|z;s\right]. \end{aligned} \tag{10}$$

We assume that retired consumers are restricted from borrowing in credit markets. Hence, the problem of a consumer age $a > N$ at date t with current bond holdings b and persistent component of income at retirement z_N is then

$$R_t(b,a,z_N) = \max_{b' \in \mathbb{R}_+} u\left(y(a,z_N) + b - q_t(b',a,z;s)b'\right) + \beta R_t(b',a',z_N), \tag{11}$$

where the terminal value is given by $R_t(b, J+1, z_N) = 0$.

3.5 Problem of the Financial Intermediary

Until this point, the two versions of our model are identical. The lone difference between them is how the financial intermediary forms expectations about future charge-off rates. In the first model, which we call *rational expectations*, financial intermediaries set spreads in a manner consistent with the existing literature. That is, the financial intermediary knows the mapping from a consumer's state variables to their repayment decision and conditions their expectations on the aggregate state of the economy. In this case, the financial intermediary is able to compute the probability that a consumer declares bankruptcy, or equivalently in our model, the charge-off rate, $h(b',a,z;s)$ on each corresponding loan contract exactly. In the second model, which we call *credit scoring*, the financial intermediary does not know the mapping from a consumer's state variables to their repayment decision and does not condition their expectations on the aggregate state of the economy. Instead, the financial intermediary learns about the charge-off rate on each corresponding loan contract over time using the realized history of charge-off rates. Given beliefs at date $t-1$, the financial intermediary revises their beliefs based on the magnitude of their forecast error and the learning gain $\gamma \in [0,1]$:

$$\mathbb{E}_t\left[h(b',a,z)\right] = \mathbb{E}_{t-1}\left[h(b',a,z)\right] + \gamma\Big(\mathrm{Ch}_t(b',a,z) - \mathbb{E}_{t-1}\left[h(b',a,z)\right]\Big), \tag{12}$$

where $\mathrm{Ch}_t(b', a, z)$ is the actual charge-off rate at date t. We employ a constant gain adaptive learning algorithm here as a recursive approximation to the actual behavior of lenders, who typically use a truncated history of past loan performance to forecast future defaults.

In both cases, competitive financial markets imply zero expected profits on each loan contract which rules out cross subsidization of interest rates across borrowers. As a result, the equilibrium bond pricing function at date t is given by

$$q_t(b', a, z; s) = \frac{1 - h(b', a, z; s)}{1 + r}, \tag{13}$$

in the rational expectations model, and

$$q_t(b', a, z) = \frac{1 - \mathbb{E}_t\left[h(b', a, z)\right]}{1 + r}, \tag{14}$$

in the credit scoring model, where $\mathbb{E}_t\left[h(b', a, z)\right]$ evolves according to equation (12). Since consumers who buy bonds never default, the price of bonds is $1/(1 + r)$ for all $b' > 0$ in both models.

The credit spread is then defined to be the average mark-up over the risk-free real interest rate r on loans made in equilibrium weighted by face value, or

$$\mathrm{CS}_t \equiv \int b'(b, a, e, z; s)\left[1/q_t(b', a, z; s) - 1 - r\right] d\Gamma_t(b, a, e, z; s), \tag{15}$$

where $\Gamma_t(b, a, e, z; s)$ represents the distribution of consumers over states at date t.

3.6 Equilibrium

A recursive competitive equilibrium consists of value functions V_t, P_t, B_t, X_t, and R_t, policy rule b'_t, and bond pricing function q_t, such that at each date t, given the sequence of aggregate states $\{s_t\}_{t=0}^{\infty}$, the value functions V_t, P_t, B_t, X_t, R_t solve equations (7) – (11) with b'_t as the resulting optimal policy rule and q_t is consistent with equation (13) in the rational expectations model or equation (14), given initial beliefs $\mathbb{E}_0\left[h\right]$, in the credit scoring model.

4 Calibration

As is standard in the business cycle literature, each model period is taken to represent one quarter of one year. Consumers are born at age 18, retire at age 65, and die with probability one at age 78. The utility function is $u(c) = c^{1-\delta}/(1-\delta)$, where δ is the coefficient of relative risk aversion which we set equal to 2. We set the risk-free real interest rate r equal to the average real return on 3 month U.S. Treasury bills during the 1990:Q1 to 2005:Q1 period, or 2.00%. According to The United States Government Accountability Office (2008), average filing costs (court and lawyer fees) under Chapter 7 totaled $900 in 2005 prior to implementation of the BAPCPA. Given median household income of approximately $46,000 in 2005, we set the fixed cost of filing bankruptcy ϕ equal to 2% of median annual income. The probability of re-entering credit markets θ is 0.0435, implying bankrupts are excluded from credit markets for 6 years on average. Next, we turn to the stochastic endowment process. We use labor income data for males in the Panel Study of Income Dynamics (2012) to estimate age dummies after controlling for occupation, education, and year-specific fixed effects. We set the deterministic function of age f_a equal to the fitted sixth-order polynomial of the estimated age dummies plotted in Figure 4.[16] We choose four aggregate states in order to smooth out the model's response to transitions between expansions and recessions. The elements of the transition matrix for the aggregate state Π are then chosen based on NBER recession dates during the post-WWII period while allowing for a transition period that averages two quarters when either entering or exiting a recession,

$$\Pi = \begin{bmatrix} 0.948 & 0.052 & 0.000 & 0.000 \\ 0.000 & 0.500 & 0.000 & 0.500 \\ 0.500 & 0.000 & 0.500 & 0.000 \\ 0.000 & 0.000 & 0.324 & 0.676 \end{bmatrix},$$

where the first row and column represent expansion, the last row and column represent recession, and the second and third rows and columns represent transitions to and from recession, respectively. We choose values for the aggregate component of income Υ_s equal to 0.0098, -0.0098, 0.0098, and -0.0098 based on the volatility of real GDP per capita observed in the data. Consumers receive transitory income shocks quarterly and persistent income shocks once a year, on average, implying that ξ is set equal to 0.25. Following Storesletten, Telmer, and Yaron (2004), the volatility of transitory income shocks σ_e is 0.175, the autocorrelation of the persistent component of income ρ is 0.957, and the volatility of persistent income shocks $\sigma_{\varepsilon,s}$ is 0.094, 0.129, 0.129, and 0.163. We discretize the transitory component into a 9–state i.i.d. process and the persistent component into a 9–state Markov chain using the methods outlined in Adda and Cooper (2003).

The final common parameters for the two versions of the model are the discount factor β and personal exemption limit ψ. To place both models on equal footing, we jointly calibrate these parameters separately within each version of the model. The discount factor β is chosen such that each model matches the average unsecured debt to income ratio during

[16] See the Appendix for details of our estimation procedure for f_a.

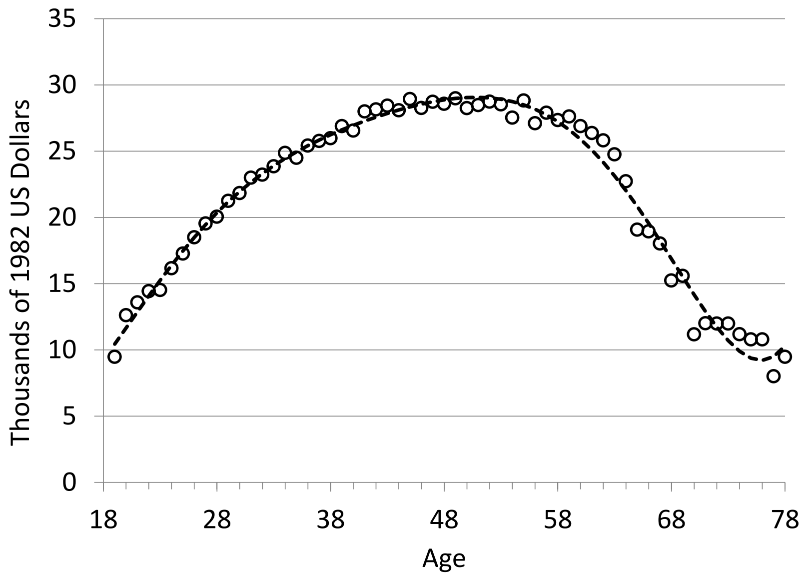


Figure 4. Estimated age dummies from the PSID and a fitted sixth-order polynomial which serves as the deterministic function of age f_a in the stochastic labor income process.

the 1990:Q1–2005:Q1 period of 0.074, and given that ψ determines the upper bound on consumption for bankrupts, we choose as a target moment the average annual bankruptcy filing rate during the same period of 5.65 filings per 1,000 adults. In principle, these parameters could have different values for the two models. Interestingly, however, we find that this calibration exercise emits identical values for β and ψ for both models, which suggests that credit scoring and rational expectations generate similar predictions for these variables in the long-run. A quarterly discount factor of 0.989 (0.957 on an annual basis) and personal exemption limit equal to 7.7% of median annual income allow both models to closely match these targeted moments in the data.[17] Table 2 summarizes our calibration exercise.

The preceding calibration is consistent across the two versions of the model, rational expectations and credit scoring. The credit scoring version of the model has one additional parameter, the learning gain, γ. When forecasting future charge-off rates in practice, lenders typically use data on loan performance that is no more than two years old in order to protect against drift in the characteristics of the population (see Thomas (2000)). To reflect this practice, we select a learning gain γ of 0.10 as a baseline calibration. This choice implies that the charge-off rate in any given quarter receives a weight of less than 5% after two

[17] According to Fay, Hurst, and White (2002), the average value of personal exemptions for bankrupts filing in 1995 was $5,000, or 14.7% of median annual income. Our model thus requires a value for ψ that is just over half of its empirical counterpart, meaning that bankruptcy in our model is more costly along this dimension compared to the real world. However, given that we abstract from all non-pecuniary costs of bankruptcy like social "stigma" (see Buckley and Brinig (1998)), we view this parameterization as reasonable.

years.[18] Given the potential importance of γ for our results, we examine the sensitivity of our findings to variations in this parameter in a later section.

Table 2: Calibration Summary

Description	Parameter Value
Retirement age (N)	65
Maximum age (J)	78
Discount factor (β)	0.989
Coefficient of relative risk aversion (δ)	2
Learning gain (γ)	0.10
Risk-free real interest rate (r)	2.00%
Probability of re-entering credit markets (θ)	4.35%
Personal exemption limit (ψ)	7.7% of median annual income
Fixed cost of filing bankruptcy (ϕ)	2.0% of median annual income
Deterministic trend (f_a)	See Figure 4
Aggregate component of income (Υ_s)	$\{0.0098, -0.0098, 0.0098, -0.0098\}$
Transitory income shock volatility (σ_e)	0.175
Autocorrelation of persistent component of income (ρ)	0.957
Probability of persistent income shock (ξ)	0.25
Persistent income shock volatility ($\sigma_{\varepsilon,s}$)	$\{0.094, 0.129, 0.129, 0.163\}$

5 Results

In this section, we compare the business cycle properties of the calibrated model in which lenders have rational expectations about future charge-off rates to its counterpart in which lenders use credit scoring to assess the credit risk of potential borrowers. We then explore the implications of employing alternative values for the learning gain parameter.

5.1 Model Fit

We begin by comparing the business cycle properties of the calibrated rational expectations model reported in Panel B of Table 3 to U.S. data between 1990:Q1 and 2005:Q1 reported in Table 1 and replicated for the reader's convenience in Panel A of Table 3. The rational expectations model is able to capture some key features of the data, including the fact that

[18]From equation (12), the charge-off rate in period t would receive a weight of $\gamma(1-\gamma)^{s-t}$ in period $s > t$.

consumption is less volatile than output as well as the facts that the spread and charge-off rate are countercyclical and are positively contemporaneously correlated. However, the model with rational expectations also misses many important aspects of the data. First, it predicts that debt is much less volatile (about 1/3 as volatile) than the data, and the spread (almost 4 times) and charge-off rate (about 3 times) are substantially more volatile than in the data. Second, while debt is weakly countercyclical in the data, the rational expectations model predicts that debt is strongly procyclical. Finally, most of the contemporaneous correlations are larger in absolute value terms compared to the data.

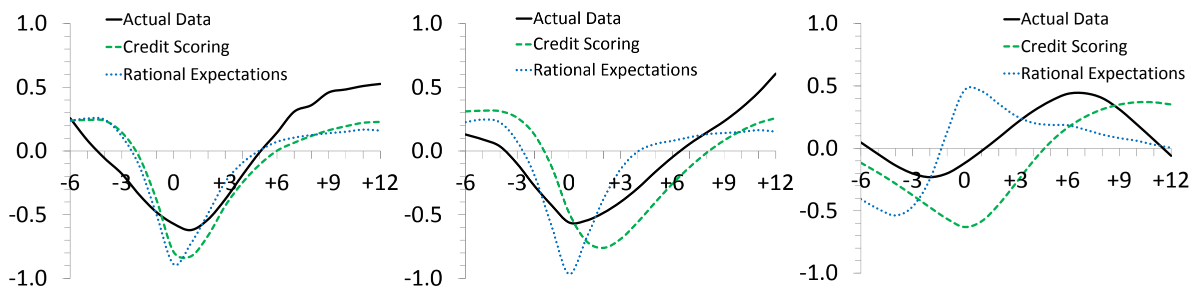
The model with credit scoring, on the other hand, is able to closely replicate many key features of the data, improving on the performance of the model with rational expectations. Credit scoring raises the volatility of debt relative to the rational expectations model, bringing it much closer to the data (2.96 in the data versus 2.12 in the model), and also reproduces the fact that debt is countercyclical, although it is more strongly countercyclical in the model than in the data (correlation with output is -0.12 in the data versus -0.63 in the model, while the correlation with consumption is -0.22 in the data versus -0.59 in the model). Credit scoring is especially effective at matching the contemporaneous correlations in the data. The credit spread is significantly negatively correlated with output (-0.48 in the model versus -0.56 in the data) and consumption (-0.69 in the model versus -0.49 in the data), and significantly positively correlated with the charge-off rate (0.86 in the model versus 0.64 in the data). Most of the remaining contemporaneous correlations have the correct signs and are quantitatively similar to their data counterparts. Although the model with credit scoring substantially reduces the volatility of the spread relative to the model with rational expectations, the spread and the charge-off rate remain larger than in the data.

Figure 5 compares the lead and lag correlations of output with the charge-off rate, credit spread, and unsecured debt implied by the calibrated models to those in the data. Both models match the lead and lag correlations between output and the charge-off rate found in the data well. The models are also similar in their implications for the lead-lag correlations between the spread and output, although the rational expectations model over-predicts the peak negative correlation and the credit scoring model predicts that the spread lags output by 2 quarters (versus 0 in the data). The most significant difference in model performance on this dimension is with the correlations between unsecured debt and output. While the model with credit scoring qualitatively matches the lead and lag correlations between debt and output, the model with rational expectations implies that debt is strongly procyclical, with positive correlations declining with further leads on unsecured debt. The credit scoring model predicts a somewhat longer lag for debt than the data, with unsecured debt lagging the cycle by 10 quarters (versus 7 in the data).

Table 3: Business Cycle Statistics, U.S. Data versus Calibrated Model

	Relative	Contemporaneous Correlations				
	Volatility	Output	Consumption	Debt	Spread	Charge-offs
Panel A: U.S. Data						
Output	1.00	1.00	0.86	-0.12	-0.56	-0.57
Consumption	0.83	0.86	1.00	-0.22	-0.49	-0.69
Debt	2.96	-0.12	-0.22	1.00	-0.30	0.20
Spread	8.77	-0.56	-0.49	-0.30	1.00	0.64
Charge-offs	14.8	-0.57	-0.69	0.20	0.64	1.00
Panel B: Rational Expectations						
Output	1.00	1.00	0.95	0.46	-0.97	-0.89
Consumption	0.63	0.95	1.00	0.50	-0.95	-0.86
Debt	0.90	0.46	0.50	1.00	-0.58	-0.58
Spread	34.3	-0.97	-0.95	-0.58	1.00	0.97
Charge-offs	42.0	-0.89	-0.86	-0.58	0.97	1.00
Panel C: Credit Scoring						
Output	1.00	1.00	0.93	-0.63	-0.48	-0.79
Consumption	0.49	0.93	1.00	-0.59	-0.69	-0.88
Debt	2.12	-0.63	-0.59	1.00	0.47	0.63
Spread	16.4	-0.48	-0.69	0.47	1.00	0.86
Charge-offs	46.3	-0.79	-0.88	0.63	0.86	1.00
Panel D: State-Contingent Credit Scoring						
Output	1.00	1.00	0.95	0.06	-0.96	-0.88
Consumption	0.59	0.95	1.00	0.15	-0.97	-0.85
Debt	0.83	0.06	0.15	1.00	-0.20	-0.14
Spread	33.1	-0.96	-0.97	-0.20	1.00	0.94
Charge-offs	41.4	-0.88	-0.85	-0.14	0.94	1.00

As a final test of the relative performance between the two models, we explore the dynamic relationships among these variables more formally by estimating the VAR in equation (1) using model-generated data. Figure 6 compares the model-implied impulse response functions from the fitted VAR to a one standard deviation increase in the charge-off rate to those implied by the data. As in the data, increases in the charge-off rate are persistent in both models, taking several quarters to dissipate completely. But while the model with rational expectations does not match the hump-shaped response of the credit spread found



(a) Charge-off Rate (b) Credit Spread (c) Unsecured Debt

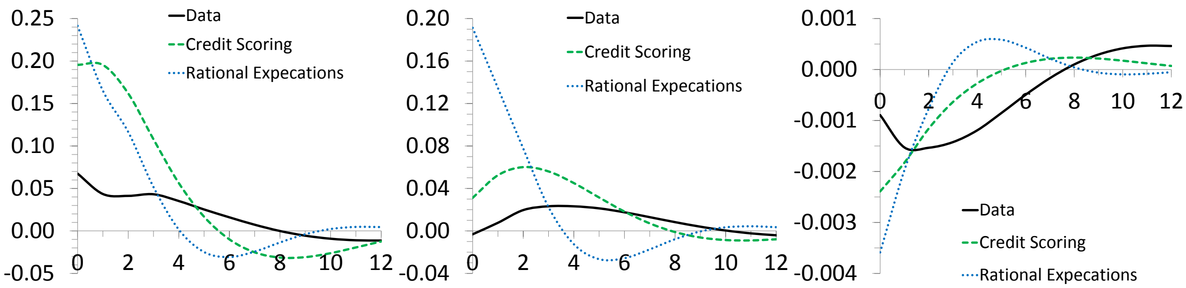
Figure 5. Lead and lag correlations with real GDP per capita.

in the data, the model with credit scoring reproduces these dynamics. The peak response of the credit spread in the model with credit scoring occurs 2 quarters after the initial shock to the charge-off rate versus 3 quarters in the data. Consistent with the data, the credit scoring model also generates a persistent rise in the credit spread, as it takes about 8 quarters for the credit spread to return back to its pre-shock level, compared to 10 quarters in the data. The model with rational expectations, on the other hand, has a peak response for the spread in the period of the shock that is substantially greater than in the data and the credit scoring model, and the rise in the spread dissipates more quickly, returning to its pre-shock level in less than a year.

These spread dynamics have important implications for the consumption response to a shock to the charge-off rate. Although the size of the charge-off rate shock is similar across models, the initial rise in the spread is much larger in the model with rational expectations, producing a larger initial drop in consumption. However, given the hump-shaped response of the credit spread in the model with credit scoring (and in the data), the rebound in consumption is much more protracted in the model with credit scoring, as a higher spread deters consumers from funding consumption through borrowing. With rational expectations, consumption returns to its pre-shock level in about 3 quarters, compared to 5 quarters with credit scoring and 7 quarters in the data.

5.2 Credit Scoring, Credit Spreads & Consumption Volatility

To understand why the credit scoring model outperforms the rational expectations alternative, it is important to recognize that a tight link between spreads, charge-off rates, and debt arises when creditors have rational expectations about future charge-off rates. In this environment, credit spreads continuously adjust to fully reflect changes in the true default risk posed by each potential borrower. Since changes in default risk are driven mainly by



(a) Charge-off Rate (b) Credit Spread (c) Consumption

Figure 6. Response to a one time, one standard deviation increase in the charge-off rate.

time-variation in income volatility, allowing lenders to condition their expectations on the aggregate state is sufficient to increase the co-movement between the charge-off rate, credit spread, unsecured debt, and consumption. It is for this reason that the model with rational expectations overstates the relative volatility of the credit spread, as well as the contemporaneous correlations between many of our variables of interest.

Credit scoring breaks this tight link between changes in true default risk and the credit spread, thereby reducing the volatility of spreads and weakening contemporaneous correlations. When lenders form expectations about future charge-off rates using the performance of past loans, credit spreads react to changes in *observed* default risk rather than changes in *anticipated* default risk. Moreover, credit scoring imparts inertia into expectations about future charge-off rates, which works to slow the response of credit spreads to contemporaneous changes in the charge-off rate. The slower credit spreads are to react to changes in macroeconomic conditions, the more effective unsecured debt is as a tool for consumption smoothing. An interesting result from this model is that while increased persistence in the credit spread means that consumption takes 1 to 2 quarters longer to recover following an increase in the charge-off rate relative to the rational expectations alternative, credit scoring reduces the relative volatility of the credit spread by 52% and the relative volatility of consumption by 22%, while also increasing the relative volatility of unsecured debt by 136%. Therefore, while rational expectations may be preferred by consumers as the economy transitions from a recession to an expansion, consumers prefer credit scoring on average because it allows unsecured debt to be used to more effectively reduce consumption volatility over the business cycle.

The way we model credit scoring can be viewed as a two-stage deviation from the rational expectations benchmark employed by standard models of consumer default. First, we assume that lenders do not condition their expectations about future charge-off rates on the aggregate state (s_t). Second, we allow lenders to forecast future charge-off rates based on the history of past charge-off rates for similar loan contracts. In order to better understand the role played by each deviation from the rational expectations benchmark, we compare our baseline model to an alternative in which creditors update their expectations about future charge-off rates in response to the history of past charge-off rates on similar loan contracts, but also condition their expectations on the aggregate state. We call this model variant *state-contingent credit scoring*. In this case, equations (12) and (14) are replaced by

$$\mathbb{E}_t\left[h(b', a, z; s)\right] = \mathbb{E}_{t-1}\left[h(b', a, z; s)\right] + \gamma\Big(\mathrm{Ch}_t(b', a, z; s) - \mathbb{E}_{t-1}\left[h(b', a, z; s)\right]\Big) \tag{16}$$

and

$$q_t(b', a, z; s) = \frac{1 - \mathbb{E}_t\left[h(b', a, z; s)\right]}{1 + r}, \tag{17}$$

respectively. In other words, expectations about future charge-off rates and bond prices are functions of the aggregate state s at the date the loan contract is issued.

Panel D of Table 3 reports the business cycle properties for the state-contingent credit scoring model. Conditioning bond prices on the aggregate state brings the baseline credit scoring model much closer to the rational expectations model along a number of dimensions. The model with state-contingent credit scoring displays significantly higher volatility for the credit spread and lower volatility for unsecured debt than the credit scoring baseline. Conditioning on the aggregate state also strengthens the contemporaneous correlations between a number of variables, including between the credit spread and output and the credit spread and consumption. These features of the model are closer to rational expectations, and further from the data, than our credit scoring baseline. Based on these results, we conclude that allowing creditors to condition on the aggregate state when setting spreads is the key feature that produces excess cyclicality and high volatility in the credit spread and low debt volatility. Removing the reliance of the spread on the aggregate state allows our baseline model to match these features of the data.

The state-contingent credit scoring model is unique in one respect – it produces unsecured debt that is acyclical. This contrasts with the baseline credit scoring model, in which unsecured debt is countercyclical as in the data, and the rational expectations alternative, in which unsecured debt is procyclical. This finding implies that the backward-looking nature of credit scoring, where spreads react to forecast errors, reduces the procylicality of debt found in the rational expectations environment.

5.3 Sensitivity Analysis

The learning gain γ in the credit scoring model determines how rapidly lenders adjust credit spreads in response to forecast errors in the charge-off rate. In this section we investigate whether our main findings are robust to alternative parameterizations of γ.

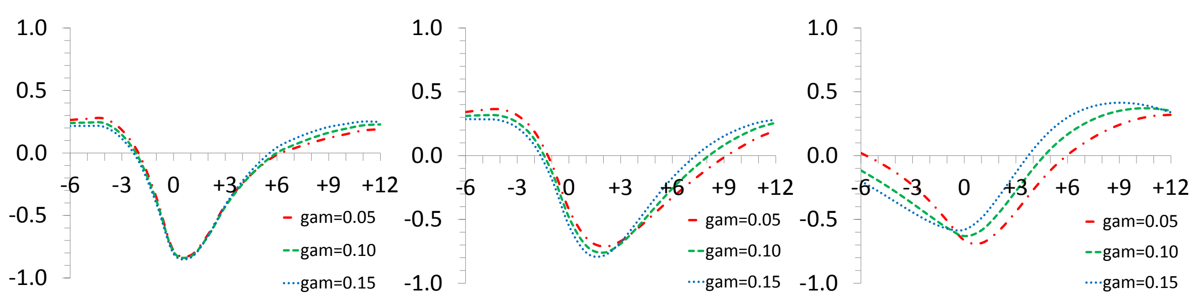
Table 4 compares the business cycle properties of our model for alternative calibrations of the learning gain parameter γ. We consider two alternatives – $\gamma = 0.05$ and $\gamma = 0.15$ – to our baseline calibration of $\gamma = 0.10$. Lower values for γ imply that creditors place greater weight on the history of past charge-off rates relative to the most recent observation when setting interest rates on loan contracts. Relative volatilities decline substantially as γ falls because creditors react more slowly to changing economic conditions. Reducing γ from 0.15 to 0.05 reduces the relative volatility of consumption by 17%, debt by 36%, credit spread by 45%, and the charge-off rate by 10%. In general, the contemporaneous correlations are only modestly affected by the choice of the learning gain, as all correlations maintain the same sign as in our baseline calibration.

Figure 7 depicts the lead-lag correlations of the charge-off rate, credit spread, and unsecured debt with output for different values of γ. The lead-lag correlations for the charge-off rate are relatively insensitive to the choice of γ. Different values for γ also have relatively limited affect on the lead-lag correlations for the credit spread and unsecured debt. The overall profile of these correlations are maintained, and the lagging relationship for the spread and unsecured debt is delayed by only one quarter as γ is reduced from 0.15 to 0.05.

Finally, Figure 8 shows the impulse response functions generated by our model for alternative calibrations of γ. Similar to our discussion about the impact on the lead-lag correlations, changing the learning gain has little impact on the dynamics of the charge-off rate. The impulse response of the credit spread continues to exhibit a hump-shaped response to a charge-off rate shock under all three parameterizations, although the magnitude of the rise diminishes as the learning gain decreases. The peak increase in the spread is about half as large when $\gamma = 0.05$ as when $\gamma = 0.15$. This result is intuitive, as the increase in the charge-off rate in the initial period has a smaller impact on expectations of future charge-off rates when creditors consider a longer history of past realizations, which is the case as γ becomes smaller. A more muted response in the credit spread allows consumption to recover more quickly for lower values of the learning gain, as consumption returns to its pre-shock level about a quarter earlier when $\gamma = 0.05$. While there are minor differences across these models, the main results presented in the previous section are robust to these plausible alternative values of γ.

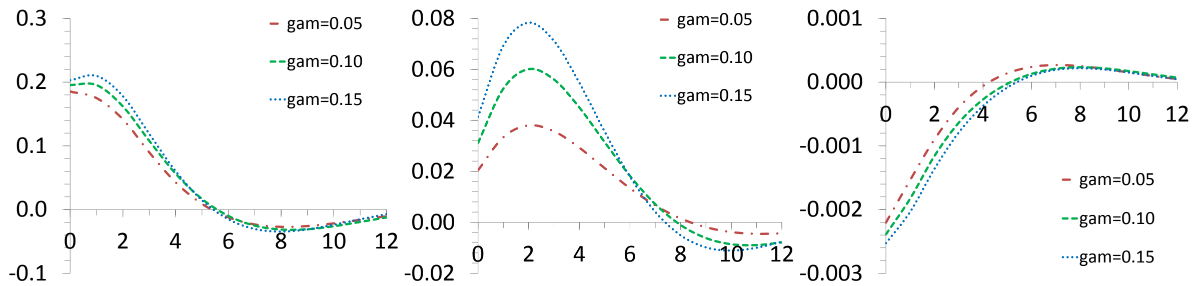
Table 4: Business Cycle Properties of the Credit Scoring Model

	Relative	Contemporaneous Correlations				
	Volatility	Output	Consumption	Debt	Spread	Charge-offs
Panel A: $\gamma = 0.05$						
Output	1.00	1.00	0.95	-0.66	-0.42	-0.78
Consumption	0.44	0.95	1.00	-0.68	-0.60	-0.85
Debt	1.55	-0.66	-0.68	1.00	0.63	0.73
Spread	11.1	-0.42	-0.60	0.63	1.00	0.82
Charge-offs	43.2	-0.78	-0.85	0.73	0.82	1.00
Panel B: $\gamma = 0.10$						
Output	1.00	1.00	0.93	-0.63	-0.48	-0.79
Consumption	0.49	0.93	1.00	-0.59	-0.69	-0.88
Debt	2.12	-0.63	-0.59	1.00	0.47	0.63
Spread	16.4	-0.48	-0.69	0.47	1.00	0.86
Charge-offs	46.3	-0.79	-0.88	0.63	0.86	1.00
Panel C: $\gamma = 0.15$						
Output	1.00	1.00	0.94	-0.58	-0.55	-0.81
Consumption	0.53	0.94	1.00	-0.49	-0.75	-0.89
Debt	2.43	-0.58	-0.49	1.00	0.35	0.54
Spread	20.1	-0.55	-0.75	0.35	1.00	0.88
Charge-offs	48.3	-0.81	-0.89	0.54	0.88	1.00



(a) Charge-off Rate (b) Credit Spread (c) Unsecured Debt

Figure 7. Lead and lag correlations with real GDP per capita generated by the credit scoring model for various values of the learning gain parameter γ.



(a) Charge-off Rate (b) Credit Spread (c) Consumption

Figure 8. Response to a one time, one standard deviation increase in the charge-off rate generated by the credit scoring model for various values of the learning gain parameter γ.

6 Conclusion

Spreads on unsecured consumer debt are volatile, strongly countercyclical, and rise persistently in response to an increase in the charge-off rate. These dynamics have important implications for consumption smoothing over the business cycle because unsecured consumer debt acts as the marginal source of financing for many consumers. Despite this important role for credit spreads, there is a tension between the backward-looking credit scoring behavior of creditors in practice and the forward-looking rational expectations behavior assumed of creditors in standard quantitative equilibrium models of consumer default.

In this paper, we ask whether rational expectations or credit scoring is better able to account for the business cycle properties of the unsecured consumer credit market. We find that modeling the credit scoring process of lenders brings the standard model with rational expectations much closer to the data on a number of important business cycle facts. In particular, credit scoring matches the volatility of the credit spread and the countercyclical nature of debt, and also improves the intertemporal dynamics of the model, including the lead-lag correlations between debt and output and the hump-shaped response of the credit spread following a shock to the charge-off rate. We also find that credit scoring slows recoveries in consumption following recessions but lowers overall consumption volatility over the business cycle relative to an environment in which lenders have rational expectations, thereby improving the usage of unsecured debt as a consumption smoothing device. Credit scoring is able to match these facts by weakening the strong link between credit spreads and the aggregate state of the economy that is present when lenders have rational expectations about future charge-off rates. Therefore, while rational expectations offers a useful benchmark for thinking about the determination of credit spreads in the market for unsecured consumer debt, our results highlight the importance of explicitly modeling the credit scoring process used by lenders in practice for generating realistic business cycle dynamics.

7 References

Adam, K. and A. Marcet (2011, May). Internal rationality, imperfect market knowledge and asset prices. *Journal of Economic Theory 146*(3), 1224–1252.

Adda, J. and R. W. Cooper (2003, August). *Dynamic Economics: Quantitative Methods and Applications*, Volume 1 of *MIT Press Books*. The MIT Press.

Athreya, K., X. S. Tam, and E. R. Young (2009). Unsecured credit markets are not insurance markets. *Journal of Monetary Economics 56*(1), 83 – 103.

Athreya, K., X. S. Tam, and E. R. Young (2012, July). A quantitative theory of information and unsecured credit. *American Economic Journal: Macroeconomics 4*(3), 153–83.

Buckley, F. H. and M. F. Brinig (1998, January). The bankruptcy puzzle. *Journal of Legal Studies 27*(1), 187–207.

Carceles-Poveda, E. and C. Giannitsarou (2008, July). Asset pricing with adaptive learning. *Review of Economic Dynamics 11*(3), 629–651.

Chatterjee, S., D. Corbae, M. Nakajima, and J.-V. Rios-Rull (2007, November). A quantitative theory of unsecured consumer credit with risk of default. *Econometrica 75*(6), 1525–1589.

Cogley, T. and T. J. Sargent (2008). Anticipated utility and rational expectations as approximations of Bayesian decision making. *International Economic Review 49*(1), 185–221.

Drozd, L. and J. Nosal (2008). Competing for customers: A search model of the market for unsecured credit. Working paper.

Eusepi, S. and B. Preston (2011, October). Expectations, learning, and business cycle fluctuations. *American Economic Review 101*(6), 2844–72.

Evans, G. and S. Honkapohja (2001). *Learning and Expectations in Macroeconomics*. Princeton University Press.

Fay, S., E. Hurst, and M. J. White (2002, June). The household bankruptcy decision. *American Economic Review 92*(3), 706–718.

Fieldhouse, D., I. Livshits, and J. MacGee (2014). Aggregate Fluctuations, Consumer Credit and Bankruptcy. Working paper.

Gordon, G. (2014, November). Evaluating default policy: The business cycle matters. *Quantitative Economics*.

Gourio, F. (2013, July). Credit risk and disaster risk. *American Economic Journal: Macroeconomics 5*(3), 1–34.

Gross, D. B. and N. S. Souleles (2002, March). An empirical analysis of personal bankruptcy and delinquency. *Review of Financial Studies 15*(1), 319–347.

Herkenhoff, K. F. (2014). The impact of consumer credit access on unemployment. Technical report.

Jagtiani, J. and W. Li (2014). Credit access after consumer bankruptcy filing: new evidence.

Kreps, D. (1998). Anticipated utility and dynamic choice. *Frontiers of Economic Theory*.

Livshits, I., J. MacGee, and M. Tertilt (2007, March). Consumer bankruptcy: A fresh start. *American Economic Review 97*(1), 402–418.

Livshits, I., J. MacGee, and M. Tertilt (2010, April). Accounting for the rise in consumer bankruptcies. *American Economic Journal: Macroeconomics 2*(2), 165–93.

Luzzetti, M. N. and S. Neumuller (2014). Income volatility, adaptive learning, and the dynamics of consumer unsecured debt and bankruptcies. Working paper.

Musto, D. K. (2004, October). What happens when information leaves a market? Evidence from postbankruptcy consumers. *Journal of Business 77*(4), 725–748.

Nakajima, M. and J.-V. Rios-Rull (2014, October). Credit, Bankruptcy, and Aggregate Fluctuations. NBER Working Papers 20617, National Bureau of Economic Research.

Panel Study of Income Dynamics (2012). *Produced and distributed by the Institute for Social Research, Survey Research Center, University of Michigan, Ann Arbor, MI*.

Sánchez, J. M. (2010). The IT revolution and the unsecured credit market. Technical report.

Sargent, T. J. (1999). *The Conquest of American Inflation*. Princeton University Press.

Storesletten, K., C. I. Telmer, and A. Yaron (2004, June). Cyclical dynamics in idiosyncratic labor market risk. *Journal of Political Economy 112*(3), 695–717.

Sullivan, J. X. (2008). Borrowing during unemployment unsecured debt as a safety net. *Journal of human resources 43*(2), 383–412.

The United States Government Accountability Office (2008). Bankruptcy reform: Dollar costs associated with the bankruptcy abuse prevention and consumer protection act of 2005. GAO-08-697.

Thomas, L. C. (2000). A survey of credit and behavioural scoring: Forecasting financial risk of lending to consumers. *International Journal of Forecasting 16*(2), 149–172.

8 Appendix

8.1 Empirical Facts

Credit markets changed dramatically between 1985 and 2014. Over this time period, use of unsecured debt nearly doubled and new bankruptcy laws introduced by Congress in 2005 under the Bankruptcy Abuse Prevention and Consumer Protection Act increased the costs associated with debt relief. In addition, the 2008–'09 recession was one of the worst on record. Given these observations, we use data from the 1990:Q1–2005:Q1 period in the main paper. Here we compare the empirical facts for this period to those derived using data from the entire 1985:Q1 to 2014:Q2 period for which data is available. Table A1 and Figures A1 and A2 report the results of this analysis. Critically, the empirical facts derived from the baseline and extended sample periods are nearly indistinguishable. A notable exception are the impulse response functions for the credit spread and consumption in Figure A2, which exhibit significantly greater persistence in response to an increase in the charge-off rate when the financial crisis is included in our sample period.

8.2 Estimating the Deterministic Income Trend (f_a)

To estimate the deterministic income trend (f_a), we use data from the merged family– and individual–level files of the Panel Study of Income Dynamics (PSID), a comprehensive longitudinal household survey that began in 1968 and includes questions pertaining to employment, income, wealth, education, and health, as well as numerous other topics. Information on individuals in the original, nationally representative sample and their descendants was collected annually through 1997 and biennially thereafter. We use data from the 1968–2009 survey years for males age 19 to 78 including years of education, an indicator for labor force participation, hours worked, occupation, and annual income (sum of wages, bonuses, commissions, overtime pay, workers compensation, and unemployment benefits).[19] Nominal labor income is deflated using the Consumer Price Index reported by the Bureau of Economic Analysis with 1982 taken as the base year. We restrict our analysis to heads of household who were in, or are descendants of, the nationally representative Survey Research Center (SRC) sample, are in the labor force, and worked at least 520 hours in the sample year.[20] This sample selection procedure yields 69,431 individual-year observations. We then regress

[19]Between 1968 and 1980, the PSID recorded occupations using various combinations of one- and two-digit codes. The 1968–1980 Retrospective Occupation-Industry Files provide 1970 Census Three-digit Codes for the occupation of each individual's main job for all sample years prior to 1981 based on a recoding of handwritten job descriptions. We use these to obtain consistent occupation categories across sample years.

[20]This restriction corresponds to 13 weeks of full-time employment and ensures that our sample consists mainly of individuals who have a strong attachment to the labor force.

the log of labor income on a series of age dummies with controls for occupation, education, and year-specific fixed effects. Table A2 reports selected results from this regression. As expected, nearly all of the age dummies are statistically significant. Finally, we fit a sixth-order polynomial to the age dummies to obtain the deterministic income trend (f_a) depicted in Figure 4. Coefficients of the polynomial representing f_a are reported in Table A3.

Table A1. Business Cycle Properties of the Unsecured Consumer Credit Market

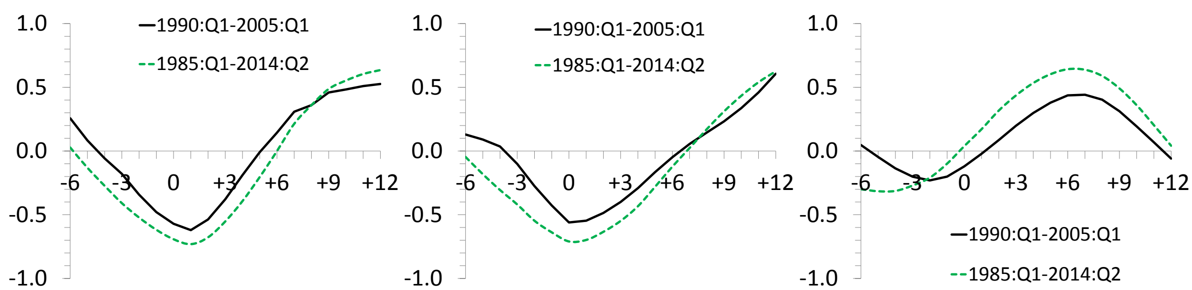
	Relative	Contemporaneous Correlations				
	Volatility	Output	Consumption	Debt	Spread	Charge-offs
Panel A: U.S. Data, 1990:Q1–2005:Q1						
Output	1.00	1.00	0.86	-0.12	-0.56	-0.57
Consumption	0.83	0.86	1.00	-0.22	-0.49	-0.69
Debt	2.96	-0.12	-0.22	1.00	-0.30	0.20
Spread	8.77	-0.56	-0.49	-0.30	1.00	0.64
Charge-offs	14.8	-0.57	-0.69	0.20	0.64	1.00
Panel B: U.S. Data, 1985:Q1–2014:Q2						
Output	1.00	1.00	0.91	0.04	-0.71	-0.69
Consumption	0.86	0.91	1.00	0.02	-0.64	-0.73
Debt	2.76	0.04	0.02	1.00	-0.14	0.04
Spread	8.15	-0.71	-0.64	-0.14	1.00	0.71
Charge-offs	16.3	-0.69	-0.73	0.04	0.71	1.00

Table A2. Fixed-effects regression results

	Coefficient	t-stat		Coefficient	t-stat		Coefficient	t-stat
Age 19	-0.130	-1.02	Age 20	0.157	1.26	Age 21	0.230	1.87
Age 22	0.291	2.38	Age 23	0.297	2.43	Age 24	0.404	3.32
Age 25	0.470	3.87	Age 26	0.539	4.43	Age 27	0.594	4.88
Age 28	0.620	5.10	Age 29	0.678	5.58	Age 30	0.705	5.80
Age 31	0.757	6.23	Age 32	0.767	6.31	Age 33	0.793	6.52
Age 34	0.835	6.86	Age 35	0.820	6.74	Age 36	0.857	7.05
Age 37	0.870	7.15	Age 38	0.878	7.22	Age 39	0.913	7.50
Age 40	0.900	7.40	Age 41	0.954	7.83	Age 42	0.959	7.87
Age 43	0.969	7.95	Age 44	0.957	7.85	Age 45	0.986	8.09
Age 46	0.963	7.90	Age 47	0.979	8.03	Age 48	0.974	7.98
Age 49	0.988	8.10	Age 50	0.962	7.88	Age 51	0.970	7.94
Age 52	0.979	8.01	Age 53	0.972	7.95	Age 54	0.936	7.65
Age 55	0.983	8.02	Age 56	0.921	7.51	Age 57	0.950	7.75
Age 58	0.930	7.57	Age 59	0.939	7.64	Age 60	0.913	7.41
Age 61	0.893	7.24	Age 62	0.872	7.02	Age 63	0.830	6.66
Age 64	0.745	5.93	Age 65	0.569	4.46	Age 66	0.563	4.32
Age 67	0.514	3.91	Age 68	0.345	2.52	Age 69	0.368	2.74
Age 70	0.035	0.25	Age 71	0.106	0.74	Age 72	0.105	0.74
Age 73	0.105	0.70	Age 74	0.036	0.24	Age 75	0.000	0.00
Age 76	(omitted)		Age 77	-0.298	-1.80	Age 78	-0.130	-0.68
Edu (yrs)	.0498	48.34	Cons	8.159	64.38			
n	69,431							
F-stat	215.63							
R^2	0.264							

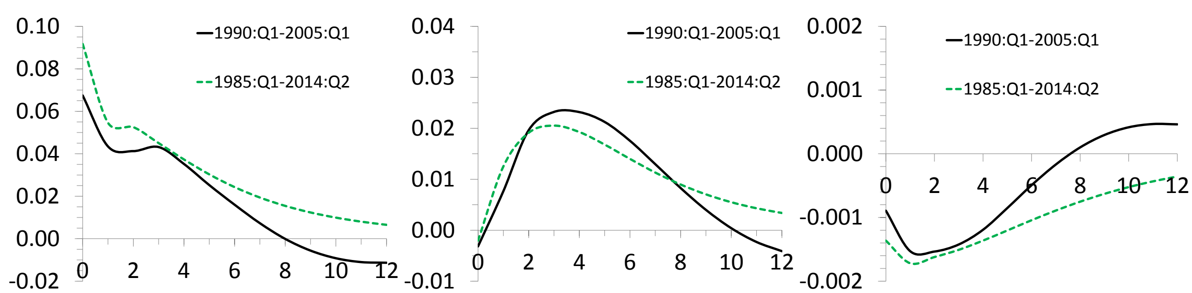
Table A3. Coefficients of f_a

Constant	64.57
Age	-13.42
$\text{Age}^2/10^2$	108.6
$\text{Age}^3/10^4$	-399.2
$\text{Age}^4/10^6$	766.6
$\text{Age}^5/10^8$	-745.5
$\text{Age}^6/10^{10}$	287.7



(a) Charge-off Rate (b) Credit Spread (c) Unsecured Debt

Figure A1. Lead and lag correlations with real GDP per capita.



(a) Charge-off Rate (b) Credit Spread (c) Consumption

Figure A2. Response to a one time, one standard deviation increase in the charge-off rate.